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Minimal-learning-parameter technique based adaptive neural control of hypersonic flight dynamics without back-stepping

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ABSTRACT

This paper investigates one robust adaptive controller for hypersonic flight dynamics. The altitude tracking is transformed into the control problem of the attitude subsystem, which is composed of flight path angle, pitch angle and pitch rate. Different from previous design using back-stepping related technique, this paper analyzed the tracking control without back-stepping where the controller is synthesized with high gain observer and minimal-learning-parameter technique. The highlight is that the design procedure is greatly simplified and the computation burden of parameter updating is reduced. It is proved that the filtered tracking error is guaranteed in the semiglobal sense. Simulation results are presented to demonstrate the effectiveness of the design.

1. Introduction

Recently hypersonic flight vehicles (HFVs) are drawing growing attention since they are intended to present a reliable and cost efficient way to access space even to launch small satellites into low earth orbit. To make the hypersonic flight available, controller design is crucial especially after the failure of X-43 in 2004 and HTV-II in 2011.

Due to the sensitivity changes in fight condition and the difficulty in measuring and estimating the aerodynamic characteristics of the vehicle, flight control design for HFVs is highly challenging. Currently flight data is not sufficient and the dynamics could not be known well enough. As a result, robust and adaptive control is widely studied on the hypersonic flight control problem [1,2] to deal with the uncertainty. The complete survey on recent progress of hypersonic flight control technology could be found in [3]. Though numerous design has been applied on hypersonic flight control, back-stepping related technique [4,5] is efficient to deal with system in cascade structure.

Currently only the longitudinal models are widely studied because of the dynamics' enormous complexity. In [6], the altitude subsystem is transformed into the strict-feedback form and the back-stepping design is adopted. In [7], the dynamics is written into the linearly parameterized form (LPF) and in [8], the dynamic surface control is proposed for the constrained dynamics. The flexible dynamics with input nonlinearity is studied with Nussbaum gain design in [9]. In [10], the intelligent control is designed using fuzzy logic system (FLS) approximating the unknown dynamics and the uniform boundedness of the closed-loop system is guaranteed.

For back-stepping related design, tedious and complex analysis is required during the determination of virtual control terms and their time derivatives. Though by letting virtual command pass through the first-order filter, dynamic surface control [8] and command filter design [11] could be employed to facilitate the design, the controller still needs n steps while at each step the virtual control is required. To make the design procedure simple, one scheme without back-stepping is keenly expected. In [12], the discrete dynamics of HFV is transformed into the prediction form by continuing looking ahead. On the basis of the prediction model [13], only with one step the controller is constructed in a much simpler way and only one neural network (NN) is required to approximate the lumped unknown dynamics. Similarly, in continuous case, by deriving the time derivative until the control input appears, one can obtain the normal output-feedback system. In [14], the altitude subsystem considering altitude, flight path angle, attack angle and pitch rate can be transformed into an output-feedback control problem.

For unknown dynamics, intelligent control [15–25] is widely analyzed using the universal approximation ability of NNs and FLS. For real application, one concern for intelligent control is on the

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computation burden of NN weights due to the large amount of NN nodes. In [26], the minimal learning design is proposed for the discrete control of hypersonic longitudinal dynamics. For continuous design, in [27] the separation principle is employed for back-stepping design with minimal-learning-parameter (MLP) technique and small gain theorem is used to prove the stability. As a result, it is really complex for the controller design and the stability analysis.

For back-stepping design of nth order system, the procedure is complex with n steps since the virtual control should be designed step by step even with dynamic surface control or command filter design which tries to simplify the design. So one concern is to simplify the structure of the controller by constructing the controller with only one step. Another problem for NN approximation is that it requires many nodes and thus lots of parameters are required to be tuned online. As a result, it is not applicable for online application especially for flight with hypersonic speed. So the other concern is to reduce the number of learning parameters. Inspired by the aforementioned discussions on simplifying design procedure and reducing the number of online parameters, this paper will focus on constructing the new control scheme for the hypersonic flight dynamics without back-stepping. The main contribution of this paper is that the minimal-learning-parameter technique is further incorporated into the high gain observer based control scheme so that there is no need to construct the virtual control and the online computation burden could be greatly reduced. In this way, the method is easy for real application especially to fulfill the hypersonic speed flight. The novel adaption law and stability analysis are presented.

This paper is organized as follows. Section 2 formulates the normal output-feedback form of the longitudinal dynamics of a generic HFV. The brief description of radial-basis-function (RBF) NN is explained in Section 3. Section 4 presents the adaptive neural controller design and the stability analysis. The simulation test is included in Section 6. Section 7 presents several comments and final remarks.

2. Problem formulation

2.1. Hypersonic flight vehicle model

The longitudinal dynamics of a generic HFV [1,28] considered in this paper is with the following equations:

$$\dot{V} = \frac{T\cos\alpha - D}{m} - \frac{\mu \sin\gamma}{r^2} \tag{1}$$

$$\dot{h} = V\sin\gamma \tag{2}$$

$$\dot{\gamma} = \frac{L + T\sin\alpha}{mV} - \frac{(\mu - V^2 r)\cos\gamma}{Vr^2} \tag{3}$$

$$\dot{\alpha} = q - \dot{\gamma} \tag{4}$$

$$\dot{q} = \frac{M_{yy}}{I_{yy}} \tag{5}$$

The model is comprised five state variables $X = [V, h, \alpha, \gamma, q]^T$ and two control inputs $U_c = [\delta_e, \beta]^T$ where V is the velocity, γ is the flight path angle, h is the altitude, α is the attack angle, q is the pitch rate.

For the notations, T, D, L and M_{yy} represent thrust, drag, lift-force and pitching moment respectively. The detail is as follows:

$$L = \tfrac{1}{2}\rho V^2 S_0 C_L, \quad D = \tfrac{1}{2}\rho V^2 S_0 C_D, \quad T = \tfrac{1}{2}\rho V^2 S_0 C_T$$
$$M_{yy} = \tfrac{1}{2}\rho V^2 S_0 \bar{c}[C_M(\alpha) + C_M(\delta_e) + C_M(q)]$$

where ρ denotes the air density, S_0 is the reference area, $\bar{c}$ is the reference length and R_E is the radius of the Earth. The mass of aircraft m, moment of inertia about pitch axis I_{yy}, gravity constant μ are constants:

$$C_L = 0.6203\alpha$$
$$C_D = 0.6450\alpha^2 + 0.0043378\alpha + 0.003772$$
$$C_T = \begin{cases} 0.02576\beta & \text{if } \beta < 1 \\ 0.0224 + 0.00336\beta & \text{otherwise} \end{cases}$$
$$C_M(\alpha) = -0.035\alpha^2 + 0.036617\alpha + 5.3261 \times 10^{-6}$$
$$C_M(q) = (q\bar{c}/2V) \times (-6.79\alpha^2 + 0.3015\alpha - 0.2289)$$
$$C_M(\delta_e) = 0.0292(\delta_e - \alpha)$$

2.2. Control goal

Given the tracking reference V_d and h_d, the control goal is to design β and δ_e to steer the system velocity and altitude to the desired trim state. With the scheme in Fig. 1, the main design is on the MLP technique based neural control of altitude subsystem without back-stepping while the similar controller is implemented on velocity subsystem.

3. Brief description of RBF NN

For the unknown nonlinearity of the system, the RBF NN [29] is employed with the following expression:

$$\hat{u}_N(X_{\text{in}}) = w^T \varphi(X_{\text{in}}) \tag{6}$$

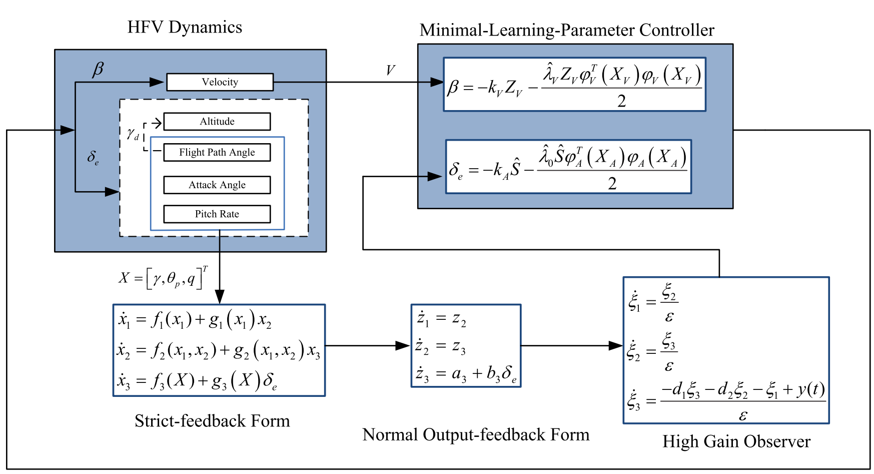

Fig. 1. Control scheme.